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Time Encoded Signal Processing and Recognition of Incipient Bearing Faults

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Abstract: **Numerous techniques for rolling bearing monitoring have been presented recently but the challenge lies in finding a reliable and price efficient monitoring system capable of providing an early alarm of bearing defects, thus, the purpose of this paper is to develop a more advanced approach using vibration signal to bearings monitoring based on TESPAR (Time Encoded Signal Processing and Recognition), the results show that TESPAR analysis when applied on its own to raw data vibration signal from different bearing conditions does not produce significant results, however, when combined with envelope signal provides an enhanced and novel method for detection of incipient bearing faults**

Keywords: Rolling bearing, vibration monitoring, condition monitoring, early alarm, TESPAR analysis, epochs.

I. INTRODUCTION

The implementation of machine condition monitoring (CM) has been growing significantly to enhance system performance and avert ruinous breakdowns. Numerous new CM methods have been proposed recently in which the key issue has been the application of efficient data analysis methods for precise determination of the machines' condition.

The paper reports a new technique to detect and identify bearing faults using TESPAR singly and in combination. TESPAR distinguishes the shapes of signal waveforms and differentiates between them. This paper reports an experimental investigation of bearing diagnosis using TESPAR with raw time-domain data, envelope analysis of the data and then combining TESPAR with envelope signal. Envelop analysis is particularly useful in extracting fault frequencies from bearings and, while using digital filtering and Fast Fourier Transforms (FFT) which require a large memory to contain all the sampled data, has produced useful results. It was chosen to combine with TESPAR because both techniques identify patterns in the data sets and thus complement each other [1].

This paper assesses the performance of the three methods for a roller bearing with three incipient faults seeded into it. It is shown that, using bearing vibration signals the combination of TESPAR and envelope analysis attains classification results that cannot be reached by either method alone.

II. TIME ENCODED SIGNAL PROCESSING AND RECOGNITION (TESPAR)

TESPAR is a digital language that originated as a means of coding signals for speech recognition [4]. TESPAR depicts signal waveforms according to its real and complex zeros based on a mathematical waveforms representation which is different from conventional CM techniques.

TESPAR quantisation procedure has been developed to code signals according to the period between two consecutive zero-crossings and the shape of the curve thus contained [6, 7]. This period is named an epoch. Every epoch can be illustrated by two parameters: D (duration - number of samples in the epoch) and S (shape – determined by the number of minima or maxima contained in the epoch). Fig. 1 shows an epoch encoded into its TESPAR parameters where D=17 and S=2.

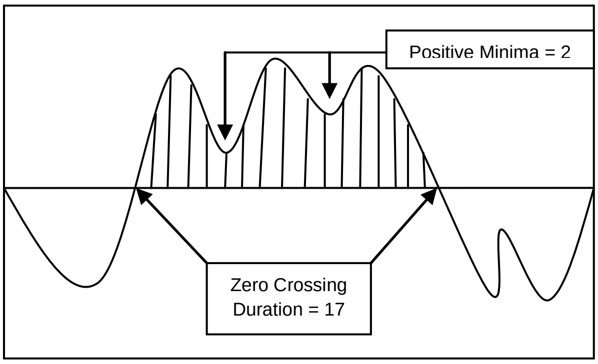

Figure 1. TESPAR single epoch with D=17, S=2

Most signal waveforms can be coded into a limited sequence of numerical descriptors known as the TESPAR symbol stream [8, 9], normally from 1 to 28. In fact 28 symbols have been found to be sufficient to describe most signals adequately. The symbol sequence can be characterised in two ways: A one-dimensional "S-Matrix" vector or two-dimensional vector which is named the "A-Matrix".

The S-matrix can be defined as the TESPAR symbols that record the number of times each TESPAR alphabet symbol occurs in the TESPAR symbol stream, and the A-matrix can be defined as a two-dimensional 28x28 vector matrix that records the number of times each pair of symbols in the alphabet appears n symbols apart in the symbol stream. The A-matrix expresses the temporal relationship between pairs of symbols [7] and because parameter n represents the delay between symbols it provides frequency information. Slowly oscillating patterns have n > 10 while higher frequency patterns have n < 10 [10].

In practice for most signal waveforms the TESPAR symbol stream is a limited sequence of numerical descriptors significantly less than 28 [8, 9].

III. BEARING TEST FACILITIES

To assess the use of TESPAR in bearing fault detection, bearing vibration data was acquired from the bearing test rig shown in Fig. 2. This consists of a 3-phase electrical induction motor combined with a dynamic brake; the stator is free to move so that torque measurements may be taken. The motor is connected to the brake through 3 shafts that are connected by two pairs of matched flexible couplings. These three shafts are held in two bearing housings, one has a cylindrical roller bearing type N406 and the other is a double row self-aligning type 22208 EK. It is the roller bearing that is tested with different faults.

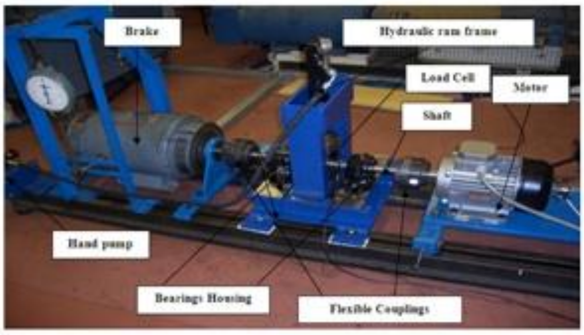

Figure 2. Bearing test rig

Table I lists the specification of the roller bearing. It is a common bearing used for high radial loads. This kind of bearing is convenient for this type of research because different faults can be easily simulated, and each fault has its characteristic frequencies.

Table I. Bearing N406 specification

Elements	Dimension	Characteristic Frequency
Roller diameter	14mm	Outer race = 83.3Hz
Rollers' number	9	Roller element = 48.3Hz
Contact angle	0˚	Inner race = 134.4Hz
Pitch diameter	59mm	Cage frequency=9.5Hz

In this paper, a healthy bearing was compared with three identical bearings, each with a fault introduced to outer race, inner race and roller element respectively. The four bearings were tested at shaft rotational speed of 1420 rpm (frequency 23.6Hz) under 50% of torsion load from a DC motor of a maximum 4.0 KW, and 5 bar of radial load that is equivalent to 433 Nm load. The faults were small scratches of 30% of the bearing width and 0.1 mm in depth which was introduced to the outer race, inner race and the roller element of three tested bearings, each bearing is with one fault. These faults are considered as incipient faults because it causes no influence on the operating performance.

IV. DATA SETS

Four experiments were performed to acquire data for four bearing conditions: healthy, inner fault, outrace fault and roller fault. Each experiment acquired data at a sampling rate of 62.5 kHz. The data length for each test was 960,000 points.

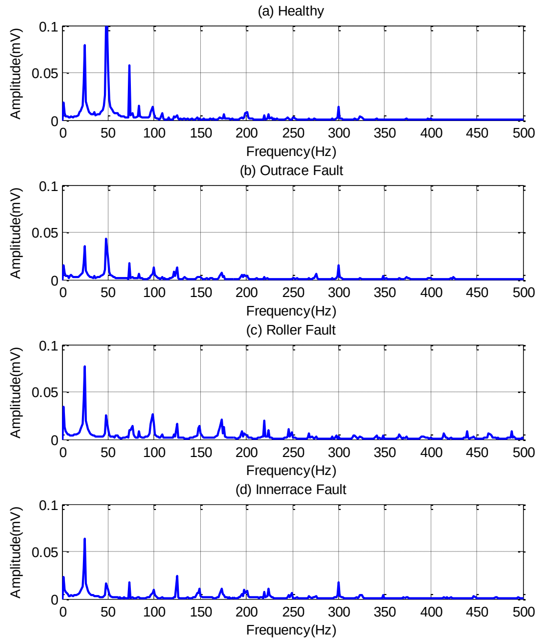

Figure 3. Raw data for a health and three small different faults

To evaluate the quality of the data, commonly used spectrum analysis is performed on the datasets which exhibit little information of the bearing in the time domain because of high noise contamination. Fig. 3 shows the data spectrum of raw data for the healthy and three small different bearings' faults. It shows that the signal is dominated by the shaft frequency at 24.3 Hz and its high order harmonics and it is difficult to identify the bearing feature frequencies from the spectrum. This shows that the bearing signal is very weak components and need to be enhanced so that the performance of TESPAR can be evaluated with good confidence.

It is well know that the most popular method for bearing monitoring is envelope analysis. Fig. 4 shows the envelope spectrum of the datasets in the frequency band from 8kHz to 15kHz. The spectra of the roller and the inner race faults are quite clear as shown in Fig. 4(c) and Fig. 4(d) respectively. The roller and the inner race characteristic faults' frequencies are identified at 48.3 Hz and 134.4 Hz respectively.

the faulty cases can be identified completely. This means that 3 feature parameters can be used directly to diagnose the faults.

However, the occurrence rates of other symbols do not show a consistent change and not suitable for separating the fault cases.

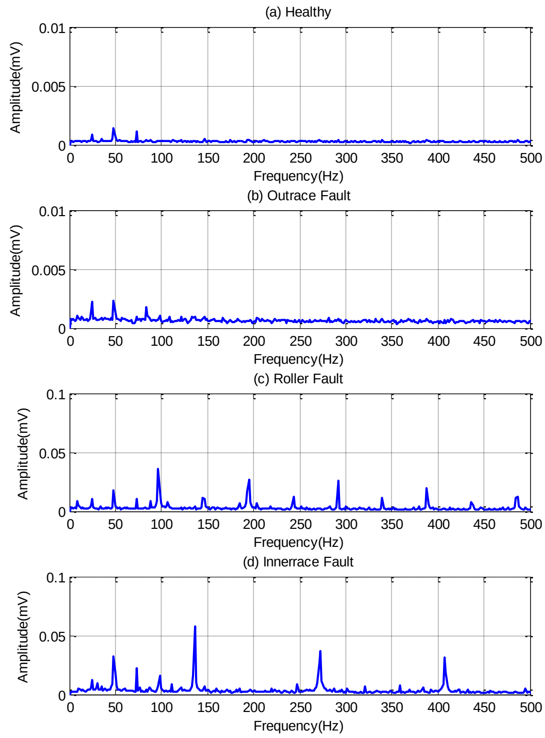

Figure 4. Envelope spectrum for a health and three different faults

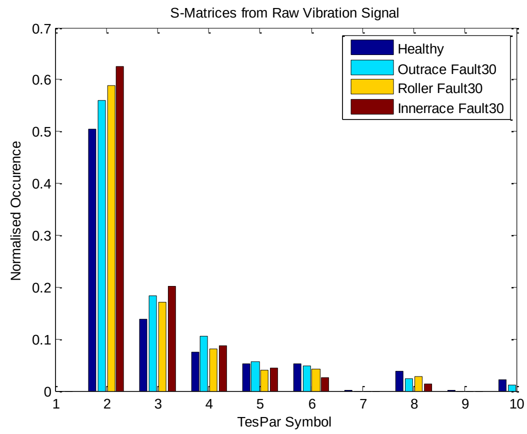

Figure 5. TESPAR S-Matrices for raw data of a healthy and three different faulty bearings

When a bearing has no fault it usually has very small vibration amplitudes in the time domain. Moreover, the characteristic frequencies cannot be seen in envelope spectrum. This can be illustrated by the blue solid line in Fig. 4(a). Compared with faulty case in the same plots, the envelope spectrum from the healthy bearing is very flat, i.e. no clear spectral lines can be seen. In Fig. 4(b) the spectra, represents the tiny outer race fault, seems to be smooth and there is insignificant amplitude which cannot be seen easily from the figure.

V. TESPAR ANALYSIS OF RAW DATA

Having confirmed that the vibration data sets include bearing faults information, they were encoded into their TESPAR symbol streams and then their S and A-Matrices were constructed by a programme written in the Matlab platform. To make comparison between different cases, the Matrices are normalised to the total number of symbols. In total, there are four sets of S-Matrices and four A-Matrices corresponding to healthy, outer race fault, roller fault and inner race fault respectively. In addition, both the raw data and the envelope data are explored with TESPAR to evaluate its noise sensitivity.

A. TESPAR S-Matrices for raw data

Comparison of the S-Matrices in Fig. 5 shows that there is a difference on TESPAR symbols 2 and 6 that is consistent with fault conditions. In particular, the occurrence rates of symbol 2, 3 and 6 are different between four bearing cases. Based on these differences,

B. TESPAR A-Matrices for raw data

The A-Matrix represents the waveform in two-dimensions, for the case n=2 the matrix shows the number of pairs two steps apart. The n attribute is known as the delay between symbols. Here n = 2, but many other A-Matrices can be formed from the same waveform by changing the value of n.

Fig. 6 shows the A-Matrices of the same bearing conditions. The patterns for the outer race and the roller faulty bearings appear very similar, where the other patterns are markedly different. From this data set is would be difficult to detect incipient outer race and roller faults using the A-Matrix.

It should be noted however, that the A-Matrix for the inner fault showed quite different pattern for the four bearings which suggests that use of the TESPAR A-Matrices with raw data could be used to detect this particular faults.

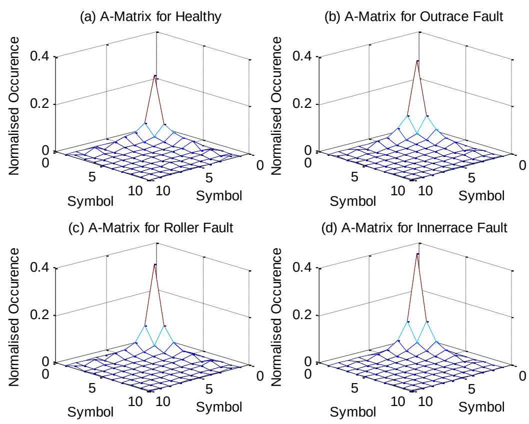

Figure 6. TESPAR A-Matrices for raw data of a healthy and three different faulty bearings

VI. TESPAR ANALYSIS WITH ENVELOPE SIGNAL

Fig. 4 shows that envelope analysis alone did not show any significant difference between the healthy bearing and the incipient outer race faulty bearing.

A. TESPAR S-Matrices for envelope signal

Fig. 7 shows the S-Matrices patterns for the combined TESPAR-envelope analysis for the reference bearing and for three different initial fault locations. Both the differences between individual symbol values and between the overall trends for the healthy bearing and the bearing with different incipient faults' locations are highly significant.

Fig. 7 shows unambiguously that the S-Matrix patterns allow clear differentiation of the healthy bearing from the incipient faulty bearings in particular the initial outer race fault which was not detected by envelope analysis independently.

However, it is also possible, based on Fig. 7 to differentiate between the initial bearings fault by using the relative values at s = 2, 5, 6 and 8 which show the best features.

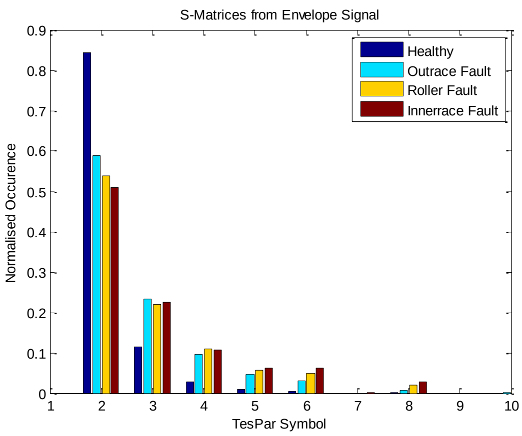

Figure 7. TESPAR S-Matrices for envelope signal of a healthy and three different faulty bearings

B. TESPAR A-Matrices for envelope signal

The patterns are discernible in the A-Matrices shown in Fig. 8, they provide clear and obvious differences for the separation between the healthy bearing and the bearings with three different initial fault locations.

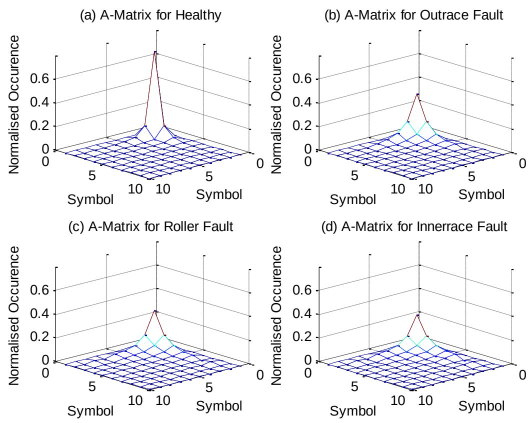

Figure 8. TESPAR A-Matrices for envelope signal of a healthy and three different faulty bearings

Trends in the patterns in A-Matrices shown in Fig. 8 provide very good features to separate fault locations. The healthy pattern has the highest amplitude where the small faulty bearings have much lower amplitudes. The outer race faulty pattern acquired higher amplitude than the other faults; in particular the inner race faulty pattern gained the lowest amplitude.

Therefore, with the introduction of faults the position of the peak changes between the different conditions as displayed in Fig 9. Since the fault causes the peak to change both in position and magnitude such changes will definitely detect incipient faults.

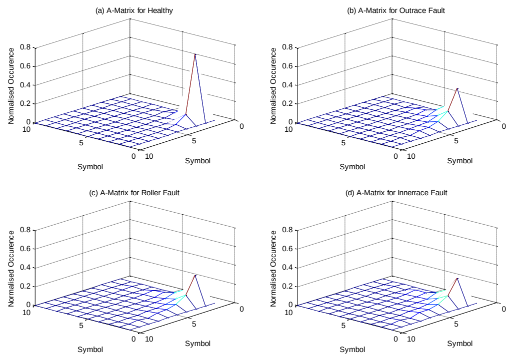

Figure 9. TESPAR A-Matrices for envelope signal of a healthy and three different faulty bearings from different angle

VII. CONCLUSION

The TESPAR performance in monitoring bearing faults has been assessed with raw data and combined with envelope signals. The results attained from TESPAR and raw signals show that S-Matrices permit fault detection; however, the A-Matrices cannot produce a full diagnosis of the data for classifying fault types. By contrast, the use of TESPAR with envelope analysis both S and A-Matrices allow full defects separation. Hence, this method is most promising and results were obtained show that the combined TESPAR with envelope approach is more sensitive than either used separately.

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